Movie Analysis

To -> Mrinal Das Sir

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PART – 1

(SHIVENDR SRIVASTAVA)

Pre – Processing

Pandas

Regex

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	id	imdb_id	popularit	budget	revenue	original_t	cast	homepag	director	tagline	keywords	overview	runtime	genres	productio	release_c	vote_cou	vote_ave	release_y	budget_a	revenue_adj
2	135397	tt036961	32.9858	1.5E+08	1.5E+09	Jurassic V	Chris Prat	http://ww	Colin Trev	The park i	monster|	Twenty-tv	124	Action|Ac	Universal	########	5562	6.5	2015	1.4E+08	1.4E+09
3	76341	tt139219	28.4199	1.5E+08	3.8E+08	Mad Max:	Tom Hard	http://ww	George M	What a Lc	future|ch	An apocal	120	Action|Ac	Village Ro	5/13/15	6185	7.1	2015	1.4E+08	3.5E+08
4	262500	tt290844	13.1125	1.1E+08	3E+08	Insurgent	Shailene	http://ww	Robert Sc	One Choic	based on	Beatrice F	119	Adventur	Summit E	3/18/15	2480	6.3	2015	1E+08	2.7E+08
5	140607	tt248849	11.1731	2E+08	2.1E+09	Star Wars	Harrison	http://ww	J.J. Abram	Every gen	android|s	Thirty yea	136	Action|Ac	Lucasfilm	12/15/15	5292	7.5	2015	1.8E+08	1.9E+09
6	168259	tt282085	9.33501	1.9E+08	1.5E+09	Furious 7	Vin Diese	http://ww	James Wa	Vengeanc	car race|	Deckard S	137	Action|Cr	Universal	########	2947	7.3	2015	1.7E+08	1.4E+09
7	281957	tt166320	9.1107	1.4E+08	5.3E+08	The Rever	Leonardo	http://ww	Alejandro	(n. One wl	father-so	In the 182	156	Western|	Regency E	12/25/15	3929	7.2	2015	1.2E+08	4.9E+08
8	87101	tt134013	8.65436	1.6E+08	4.4E+08	Terminat	Arnold Sc	http://ww	Alan Tayl	Reset the	saving the	The year i	125	Science Fi	Paramou	6/23/15	2598	5.8	2015	1.4E+08	4.1E+08
9	286217	tt365938	7.6674	1.1E+08	6E+08	The Marti	Matt Dam	http://ww	Ridley Sc	Bring Him	based on	During a r	141	Drama|A	Twentiet	9/30/15	4572	7.6	2015	9.9E+07	5.5E+08
10	211672	tt229364	7.40416	7.4E+07	1.2E+09	Minions	Sandra Bu	http://ww	Kyle Bald	Before Gr	assistant	Minions S	91	Family|Ar	Universal	6/17/15	2893	6.5	2015	6.8E+07	1.1E+09
11	150540	tt209667	6.3268	1.8E+08	8.5E+08	Inside Ou	Amy Poeh	http://mo	Pete Doct	Meet the	dream|ca	Growing u	94	Comedy|/	Walt Disn	########	3935	8	2015	1.6E+08	7.9E+08
12	206647	tt237971	6.20028	2.5E+08	8.8E+08	Spectre	Daniel Cr	http://ww	Sam Men	A Plan No	spy|base	A cryptic r	148	Action|Ac	Columbia	10/26/15	3254	6.2	2015	2.3E+08	8.1E+08
13	76757	tt161766	6.18937	1.8E+08	1.8E+08	Jupiter As	Mila Kuni	http://ww	Lana Wac	Expand yc	jupiter|sp	In a unive	124	Science Fi	Village Ro	########	1937	5.2	2015	1.6E+08	1.7E+08
14	264660	tt047075	6.11885	1.5E+07	3.7E+07	Ex Machir	Domhnall	http://exr	Alex Garla	There is n	dancing|a	Caleb, a 2	108	Drama|Sc	DNA Films	1/21/15	2854	7.6	2015	1.4E+07	3.4E+07
15	257344	tt212012	5.985	8.8E+07	2.4E+08	Pixels	Adam San	http://ww	Chris Colu	Game On.	video gan	Video gan	105	Action|Cc	Columbia	7/16/15	1575	5.8	2015	8.1E+07	2.2E+08
16	99861	tt239542	5.94493	2.8E+08	1.4E+09	Avengers:	Robert Dc	http://ma	Joss Whe	A New Age	marvel co	When Tor	141	Action|Ac	Marvel St	4/22/15	4304	7.4	2015	2.6E+08	1.3E+09
17	273248	tt346025	5.8984	4.4E+07	1.6E+08	The Hatef	Samuel L.	http://the	Quentin T	No one co	bounty hu	Bounty hu	167	Crime|Dr	Double Fe	12/25/15	2389	7.4	2015	4E+07	1.4E+08
18	260346	tt244604	5.74976	4.8E+07	3.3E+08	Taken 3	Liam Nee	http://ww	Olivier Me	It Ends He	revenge|	Ex-govern	109	Crime|Ac	Twentiet	########	1578	6.1	2015	4.4E+07	3E+08
19	102899	tt047897	5.57318	1.3E+08	5.2E+08	Ant-Man	Paul Rudc	http://ma	Peyton Re	Heroes D	marvel co	Armed wi	115	Science Fi	Marvel St	7/14/15	3779	7	2015	1.2E+08	4.8E+08
20	150689	tt166119	5.55682	9.5E+07	5.4E+08	Cinderell	Lily James|Cate Bla		Kenneth E	Midnight	cinderell	When her	112	Romance	Walt Disn	########	1495	6.8	2015	8.7E+07	5E+08
21	131634	tt195126	5.47696	1.6E+08	6.5E+08	The Hung	Jennifer L	http://ww	Francis La	The fire w	revolutio	With the	136	War|Adve	Studio Ba	11/18/15	2380	6.5	2015	1.5E+08	6E+08
22	158852	tt196441	5.46214	1.9E+08	2.1E+08	Tomorrov	Britt Robe	http://mo	Brad Bird	Imagine a	inventor|	Bound by	130	Action|Fa	Walt Disn	5/19/15	1899	6.2	2015	1.7E+08	1.9E+08
23	307081	tt179868	5.33706	3E+07	9.2E+07	Southpaw	Jake Gyllenhaal|Ra		Antoine F	Believe in	sport	Billy "The	123	Action|Dr	Escape Ar	6/15/15	1386	7.3	2015	2.8E+07	8.4E+07
24	254128	tt212635	4.90783	1.1E+08	4.7E+08	San Andre	Dwayne J	http://ww	Brad Peyt	A rescue p	california	In the afte	114	Action|Dr	New Line	5/27/15	2060	6.1	2015	1E+08	4.3E+08
25	216015	tt232244	4.7104	4E+07	5.7E+08	Fifty Shad	Dakota Jo	https://w	Sam Taylc	Are you cu	based on	When col	125	Drama|R	Focus Fea	########	1865	5.3	2015	3.7E+07	5.2E+08
26	318846	tt159636	4.64805	2.8E+07	1.3E+08	The Big Sh	Christian	http://ww	Adam Mc	This is a t	bank|frau	The men v	130	Comedy|I	Paramou	########	1545	7.3	2015	2.6E+07	1.2E+08
27	177677	tt238124	4.56671	1.5E+08	6.8E+08	Mission: I	Tom Cruis	http://ww	Christoph	Desperat	spy|sequ	Ethan anc	131	Action	Paramou	7/23/15	2349	7.1	2015	1.4E+08	6.3E+08
28	214756	tt263727	4.56455	6.8E+07	2.2E+08	Ted 2	Mark Wahlberg|Set		Seth Mac	Ted is Cor	sperm ba	Newlywe	115	Comedy	Universal	6/25/15	1666	6.3	2015	6.3E+07	2E+08

```
print(movies_df.isnull().sum())
```

```
id                        0
imdb_id                  10
popularity                0
budget                    0
revenue                   0
original_title            0
cast                     76
homepage               7930
director                 44
tagline                2824
keywords               1493
overview                  4
runtime                   0
genres                   23
production_companies   1030
release_date              0
vote_count                0
vote_average              0
release_year              0
budget_adj                0
revenue_adj               0
dtype: int64
```

Null Values

Total 7 columns of them

Replaced them with "N/A"

```
print(movies_df.isnull().sum())
```

```
id                     0
imdb_id                0
popularity             0
budget                 0
revenue                0
original_title         0
cast                   0
homepage               0
director               0
tagline                0
keywords               0
overview               0
runtime                0
genres                 0
production_companies   0
release_date           0
vote_count             0
vote_average           0
release_year           0
budget_adj             0
revenue_adj            0
dtype: int64
```

Multiple type of Date Formats

	release_date	date_format
0	6/9/15	DD.MM.YY
1	5/13/15	DD.MM.YY
2	3/18/15	DD.MM.YY
3	12/15/15	MM/DD/YY
4	4/1/15	DD.MM.YY
...	...	...
10861	6/15/66	DD.MM.YY
10862	12/21/66	MM/DD/YY
10863	1/1/66	DD.MM.YY
10864	11/2/66	DD.MM.YY
10865	11/15/66	MM/DD/YY

[10866 rows x 2 columns]
Unique date formats: ['DD.MM.YY' 'MM/DD/YY']

```
formats = {
    r'^\d{4}-\d{2}-\d{2}$': 'YYYY-MM-DD',
    r'^\d{2}/\d{2}/\d{4}$': 'MM/DD/YYYY',
    r'^\d{2}/\d{2}/\d{2}$': 'MM/DD/YY',
    r'^\d{1,2}\s\w+\s\d{4}$': 'DD Month YYYY',
    r'^\d{1,2}.\d{1,2}.\d{4}$': 'DD.MM.YYYY',
    r'^\d{4}.\d{1,2}.\d{1,2}$': 'YYYY.MM.DD',
    r'^\d{1,2}.\d{1,2}.\d{2}$': 'DD.MM.YY',
    r'^\w+\s\d{1,2},\s\d{4}$': 'Month DD, YYYY',
    r'^\w+\s\d{1,2}th,\s\d{4}$': 'Month DDth, YYYY',
}
```

	release_date	date_format
0	2015-06-09	YYYY-MM-DD
1	2015-05-13	YYYY-MM-DD
2	2015-03-18	YYYY-MM-DD
3	2015-12-15	YYYY-MM-DD
4	2015-04-01	YYYY-MM-DD
...	...	...
10861	2066-06-15	YYYY-MM-DD
10862	2066-12-21	YYYY-MM-DD
10863	2066-01-01	YYYY-MM-DD
10864	2066-11-02	YYYY-MM-DD
10865	2066-11-15	YYYY-MM-DD

[10866 rows x 2 columns]
Unique date formats: ['YYYY-MM-DD']

Replaced them to only one single type of Date-Time format

genres	production_companies
Action|Adventure|Science Fiction|Thriller	Universal Studios|Amblin Entertainment|Legenda...
Action|Adventure|Science Fiction|Thriller	Village Roadshow Pictures|Kennedy Miller Produ...
Adventure|Science Fiction|Thriller	Summit Entertainment|Mandeville Films|Red Wago...
Action|Adventure|Science Fiction|Fantasy	Lucasfilm|Truenorth Productions|Bad Robot

Values Separated by "|"

Total 5 columns of them

Replaced them with ","

genres	produ
ure, Science Fiction, Thriller	Universal Studios, Amb
ure, Science Fiction, Thriller	Village Roadshow Pictur
ence Fiction, Thriller	Summit Entertainment, Ma
ure, Science Fiction, Fantasy	Lucasfilm, Truenorth Produ

```
movies_df['genres'] = movies_df['genres'].apply(lambda g: g.replace('|', ', '))
movies_df['production_companies']= movies_df['production_companies'].apply(lambda x: x.replace('|', ', '))
movies_df['cast']= movies_df['cast'].apply(lambda c: c.replace('|', ', '))
movies_df['director']= movies_df['director'].apply(lambda c: c.replace('|', ', '))
movies_df['keywords']= movies_df['keywords'].apply(lambda c: c.replace('|', ', '))
comma_sep = movies_df.loc[:, ['genres', 'production_companies', 'cast','director']]
comma_sep.head()
```

```
movies_df['popularity'].head()
```

```
0    32.985763
1    28.419936
2    13.112507
3    11.173104
4     9.335014
```

Popularity being Non-Normalized

```
movies_df['popularity']=1+9*(movies_df['popularity'] -
                movies_df['popularity'].min())/(movies_df['popularity'].max()-movies_df['popularity'].min())
movies_df['popularity'].head()
```

Pythor

```
0    10.000000
1     8.754235
2     4.577671
3     4.048514
4     3.546999
Name: popularity, dtype: float64
```

```python
# Original strings with encoding issues
encoded_names = [
    "Alejandro GonzÃƒÂ¡lez IÃƒÂ±ÃƒÂ¡rritu",
    "KryÃ…Â¡tof HÃƒÂ¡dek",
    "Aki KaurismÃƒÂ¤ki",
    "JosÃƒÂ© ZÃƒÂºÃƒÂ±iga",
    "Cheung Yam-Yim",
    "Ã€lex BrendemÃ¼hl",
    "TÃ³mas Lemarquis",
    "Irene MontalÃ",
    "FÃ©lix GÃ³mez",
    "Ã‰tienne Chatiliez",
    "Ã‡aÄŸan Irmak",
    "JiÅ™Ã Menzel"
]
```

Some Different special Characters present in Director Column Names

Very hard to pronounce and even read for english readers

```python
def clean_encoded_name(encoded_name):
    cleaned_name = encoded_name.replace("Ã¼", "ü")  \
                               .replace("Å¡", "š") \
                               .replace("Ã€", "Ãe")  \
                               .replace("ÃƒÂ©", "é") \
                               .replace("ÃƒÂº", "ú") \
                               .replace("ÃƒÂ¡", "á") \
                               .replace("ÃƒÂ±", "ñ") \
                               .replace("ÃƒÂ", "Ó") \
                               .replace("ÃƒÂ¡", "á") \
                               .replace("ÃƒÂº", "ú") \
                               .replace("ÃƒÂ¡", "á") \
                               .replace("ÃƒÂ½", "ý") \
                               .replace("ÃƒÂ¤", "ä") \
                               .replace("Ã¡", "á") \
                               .replace("Ã", "í") \
                               .replace("Ã¡", "á") \
                               .replace("Ã©", "é") \
                               .replace("Ã“", "Ó") \
                               .replace("Ã‰", "É") \
                               .replace("Ã–", "Ö") \
                               .replace("Ã‡", "Ç") \
                               .replace("ÄŸ", "ğ") \
                               .replace("Å™", "ř") \
                               .replace("Ã", "í")  \
                               .replace("Ã³", "ó")
```

Replacement taken from :

Google (similar readable english letter)

WikiPedia (similar readable english letter)

IMDB (actual english readable names of directors)

```python
# Original strings with encoding issues
encoded_names = [
    "Alejandro GonzÃƒÂ¡lez IÃƒÂ±ÃƒÂ¡rritu",
    "KryÃ…Â¡tof HÃƒÂ¡dek",
    "Aki KaurismÃƒÂ¤ki",
    "JosÃƒÂ© ZÃƒÂºÃƒÂ±iga",
    "Cheung Yam-Yim",
    "Ã€lex BrendemÃ¼hl",
    "TÃ³mas Lemarquis",
    "Irene MontalÃ",
    "FÃ©lix GÃ³mez",
    "Ã‰tienne Chatiliez",
    "Ã‡aÄŸan Irmak",
    "JiÅ™Ã Menzel"
]
```

```
Alejandro González Iñárritu
Kryštof Hádek
Aki KaurismÓ¤ki
José Zúñiga
Cheung Yam-Yim
Ålex Brendemühl
Tómas Lemarquis
Irene MontalÃ
Félix Gómez
Étienne Chatiliez
Çağan Irmak
Jiří Menzel
```

Same Process of Renaming Names Containing special characters were done for :

Directors

Actors

Production Companies

Keywords

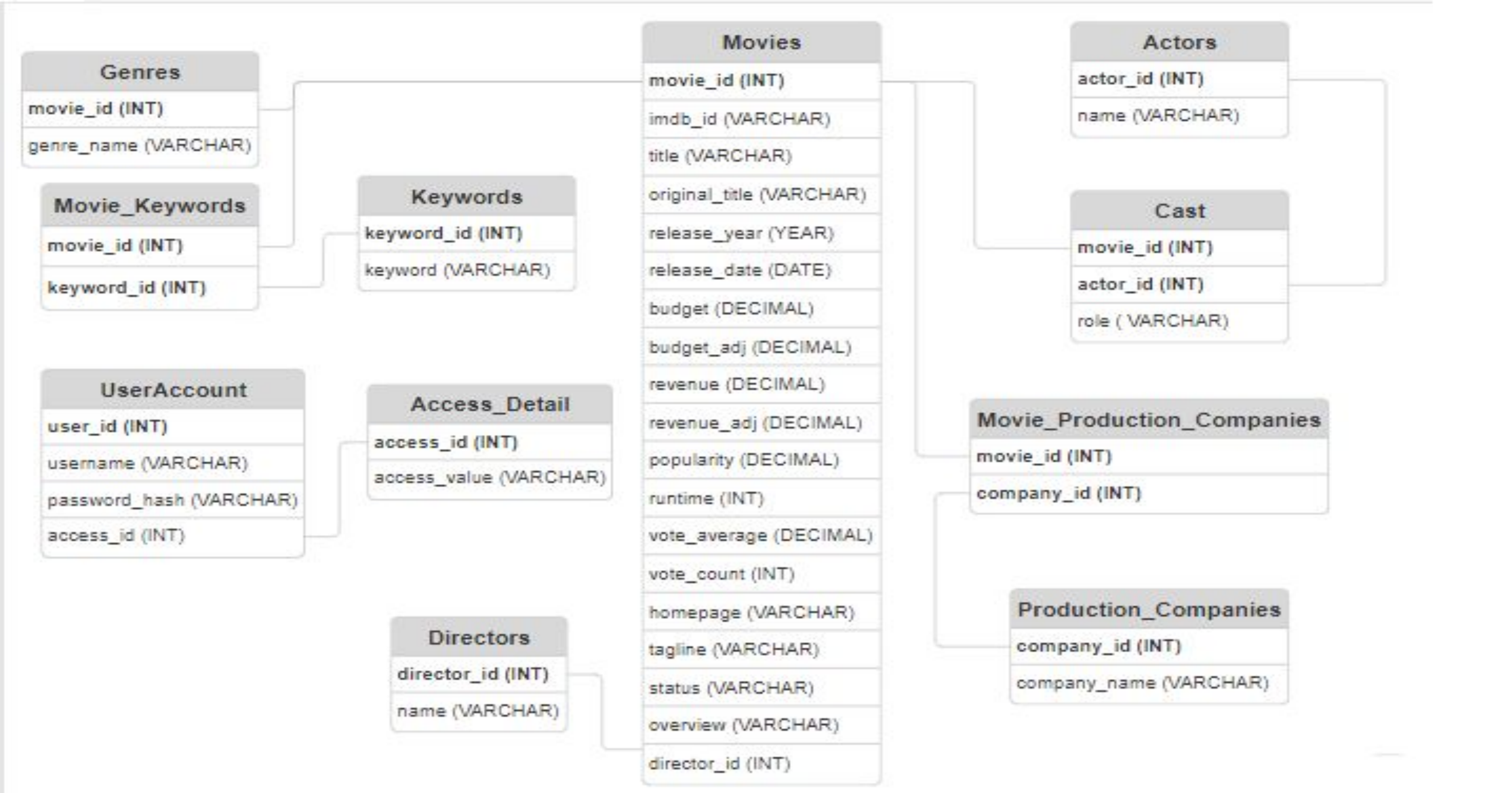
DataBase Schema Creation

SQLAlchemy

psycopg2

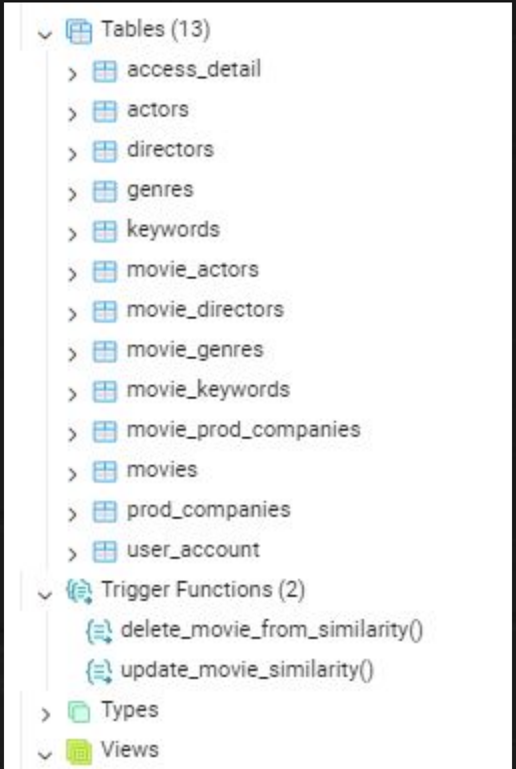
	id	imdb_id	popularity	budget	revenue	original_title
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens

DB DESIGN



Genres
movie_id (INT)
genre_name (VARCHAR)
Movie_Keywords
movie_id (INT)
keyword_id (INT)
Keywords
keyword_id (INT)
keyword (VARCHAR)
UserAccount
user_id (INT)
username (VARCHAR)
password_hash (VARCHAR)
access_id (INT)
Access_Detail
access_id (INT)
access_value (VARCHAR)
Directors
director_id (INT)
name (VARCHAR)
Movies
movie_id (INT)
imdb_id (VARCHAR)
title (VARCHAR)
original_title (VARCHAR)
release_year (YEAR)
release_date (DATE)
budget (DECIMAL)
budget_adj (DECIMAL)
revenue (DECIMAL)
revenue_adj (DECIMAL)
popularity (DECIMAL)
runtime (INT)
vote_average (DECIMAL)
vote_count (INT)
homepage (VARCHAR)
tagline (VARCHAR)
status (VARCHAR)
overview (VARCHAR)
director_id (INT)
Actors
actor_id (INT)
name (VARCHAR)
Cast
movie_id (INT)
actor_id (INT)
role (VARCHAR)
Movie_Production_Companies
movie_id (INT)
company_id (INT)
Production_Companies
company_id (INT)
company_name (VARCHAR)

DB DESIGN



11 Tables for Movie DataBase

2 Tables For User Account and Access Details

DB DESIGN

11 Tables for Movie DataBase

Actors , Directors , Genres, Keywords, Production Companies
-> These all 5 had multiple values inside one column .
Hence , separated them out with new each new table for each unique name = 5 tables

And For each of them another table to represent their relationship with the movie ID = 5 tables

One last table containing all the remaining non-redundant columns (movie table) = 1 Table

DB DESIGN

Table (movie_prod_companies)	:	[movie_id , prod_comp_id]
Table (prod_companies)	:	[ID , Name]
Table (movie_directors)	:	[movie_id , director_id]
Table (directors)	:	[ID , Name]
Table (movie_genres)	:	[movie_id , genre_id]
Table (genres)	:	[ID , Name]
Table (movie_actors)	:	[movie_id , actor_id]
Table (actors)	:	[ID , Name]
Table (movie_keywords)	:	[movie_id , keyword_id]
Table (keywords)	:	[ID , Name]
Table (movies)	:	['id','imdb_id','popularity', 'budget', 'revenue', 'original_title', 'homepage', 'tagline', 'overview', 'runtime', 'release_date', 'vote_count', 'vote_average', 'release_year', 'budget_adj', 'revenue_adj']

DB DESIGN

```python
table_name = 'keywords'
keyword_df.to_sql(table_name, engine, if_exists='replace', index=False)

print(f"Data successfully inserted into the '{table_name}' table in the '{db_name}' database!")
```

```
Data successfully inserted into the 'keywords' table in the 'movies_de_database' database!
```

```python
table_name = 'movie_keywords'
movie_keyword_df.to_sql(table_name, engine, if_exists='replace', index=False)

print(f"Data successfully inserted into the '{table_name}' table in the '{db_name}' database!")
```

```
Data successfully inserted into the 'movie_keywords' table in the 'movies_de_database' database!
```

```python
table_name = 'actors'
actor_df.to_sql(table_name, engine, if_exists='replace', index=False)

print(f"Data successfully inserted into the '{table_name}' table in the '{db_name}' database!")
```

```
Data successfully inserted into the 'actors' table in the 'movies_de_database' database!
```

Made appropriate DataFrames and directly send them to database as creating tables with complete data

VIEW (REMOVED)

Query Query History

```sql
CREATE EXTENSION IF NOT EXISTS pg_trgm;

-- DROP MATERIALIZED VIEW IF EXISTS movie_similarity;


CREATE MATERIALIZED VIEW IF NOT EXISTS movie_similarity AS
SELECT
    LEAST(m1.id, m2.id) AS movie_id_1,
    GREATEST(m1.id, m2.id) AS movie_id_2,
    similarity(m1.original_title, m2.original_title) AS similarity_score
FROM movies m1
JOIN movies m2 ON m1.id != m2.id
WHERE similarity(m1.original_title, m2.original_title) > 0.5
AND similarity(m1.original_title, m2.original_title) < 1;
```

```sql
CREATE TABLE IF NOT EXISTS movie_similarity (
    movie_id_1 INT,
    movie_id_2 INT,
    similarity_score REAL,
    PRIMARY KEY (movie_id_1, movie_id_2)
);
```

TRIGGER

Query | Query History

```sql
CREATE OR REPLACE FUNCTION delete_movie_from_similarity()
RETURNS TRIGGER AS $$
BEGIN
    DELETE FROM movie_similarity
    WHERE movie_id_1 = OLD.id OR movie_id_2 = OLD.id;

    RETURN OLD;
END;
$$ LANGUAGE plpgsql;


CREATE OR REPLACE TRIGGER after_movie_delete
AFTER DELETE ON movies
FOR EACH ROW
EXECUTE FUNCTION delete_movie_from_similarity();
```

Query | Query History

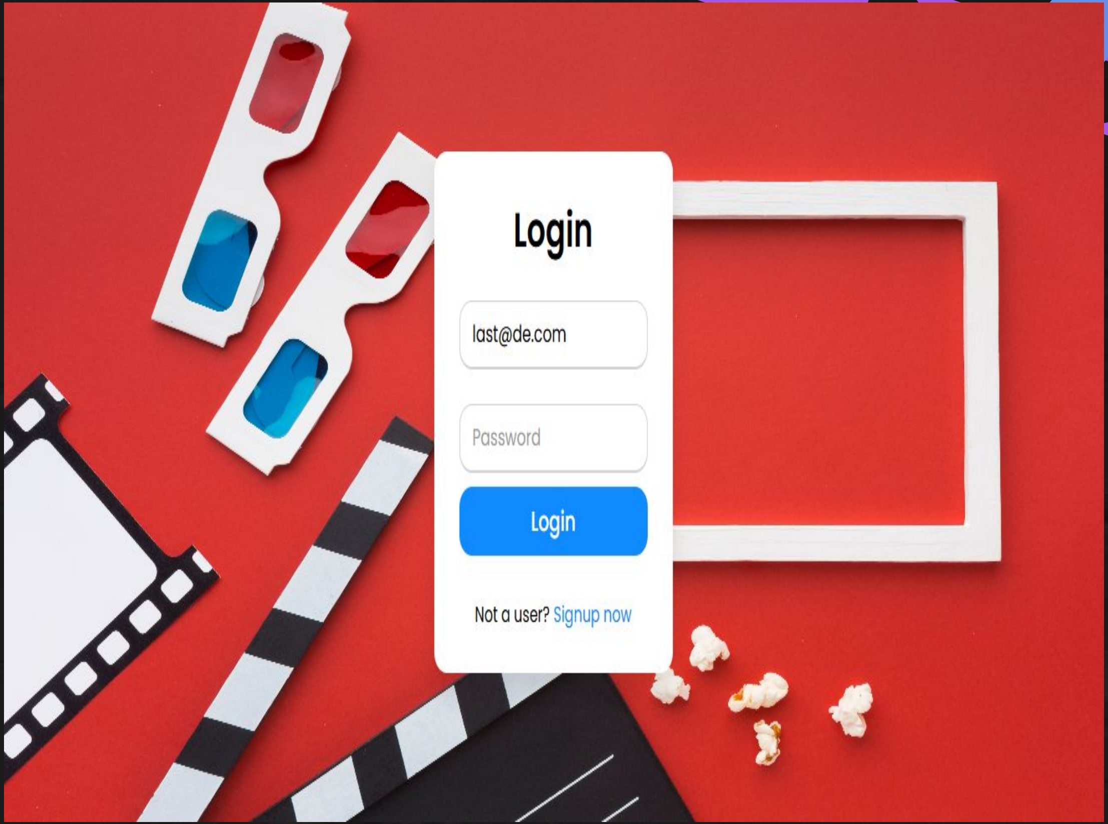
```sql
CREATE OR REPLACE FUNCTION update_movie_similarity()
RETURNS TRIGGER AS $$
BEGIN
    INSERT INTO movie_similarity (movie_id_1, movie_id_2, similarity_score)
    SELECT
        LEAST(NEW.id, m.id) AS movie_id_1,
        GREATEST(NEW.id, m.id) AS movie_id_2,
        similarity(NEW.original_title, m.original_title) AS similarity_score
    FROM movies m
    WHERE NEW.id != m.id
      AND similarity(NEW.original_title, m.original_title) > 0.5
      AND similarity(NEW.original_title, m.original_title) < 1;

    RETURN NEW;
END;
$$ LANGUAGE plpgsql;


CREATE OR REPLACE TRIGGER after_movie_insert
AFTER INSERT ON movies
FOR EACH ROW
EXECUTE FUNCTION update_movie_similarity();
```

PART – 2

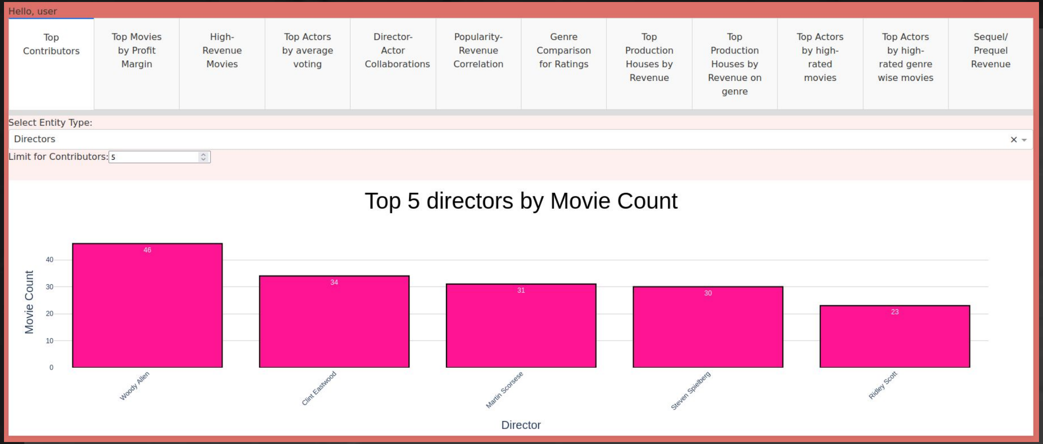
(SUDHIN S)

Implementation

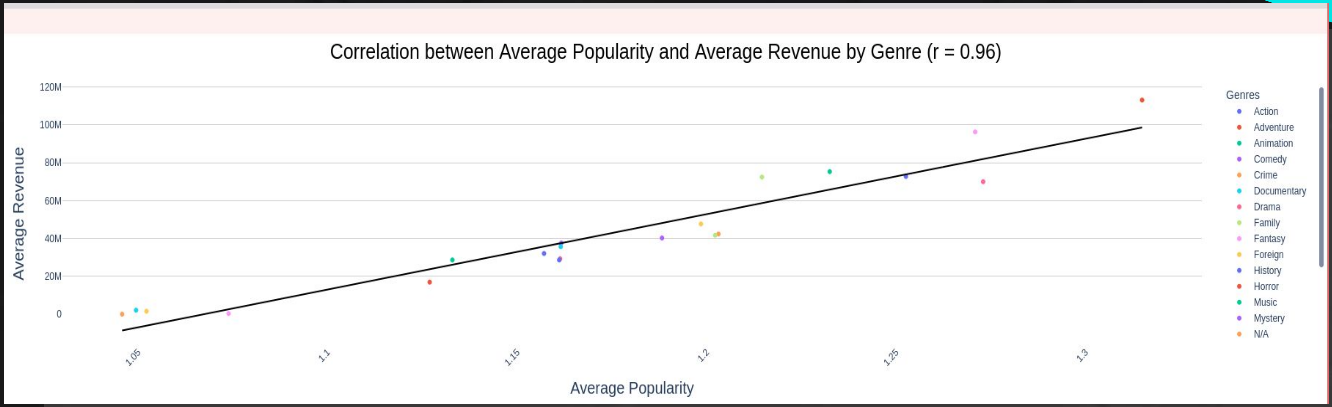
Flask
DASH
PlotLY
PSYCOPG2
SQLAlchemy

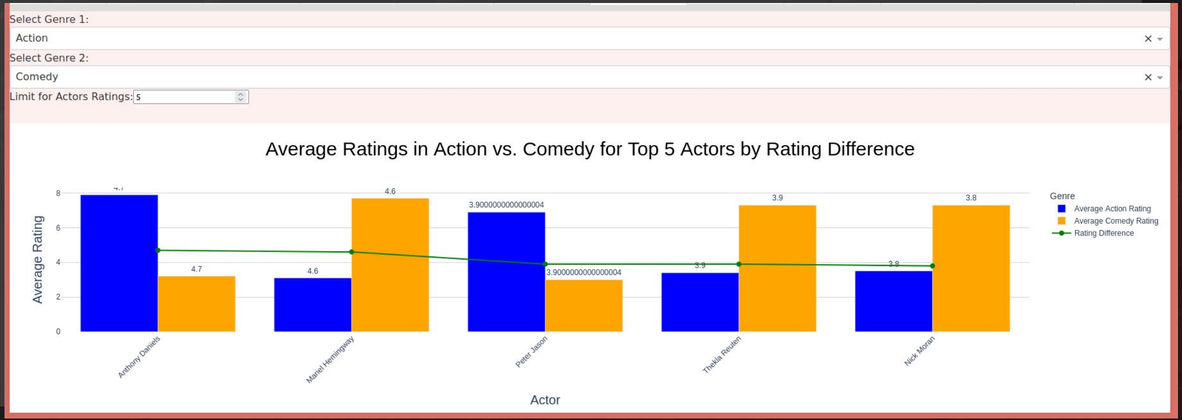


Data Visualizations

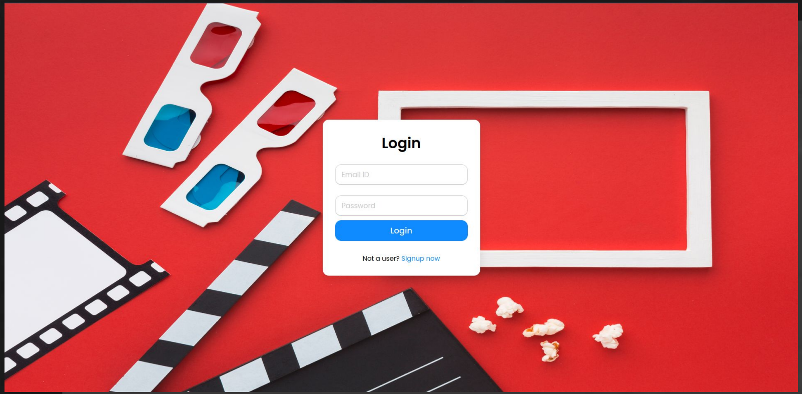


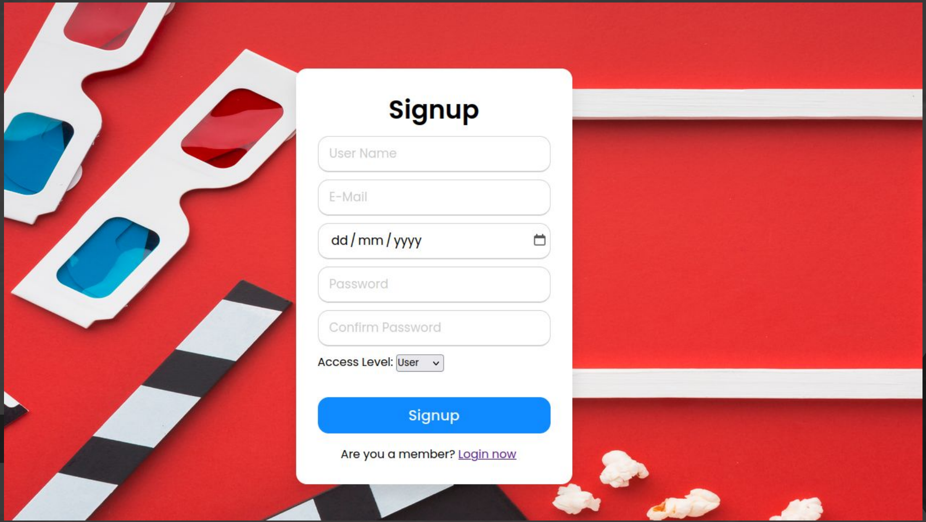
Data Visualizations



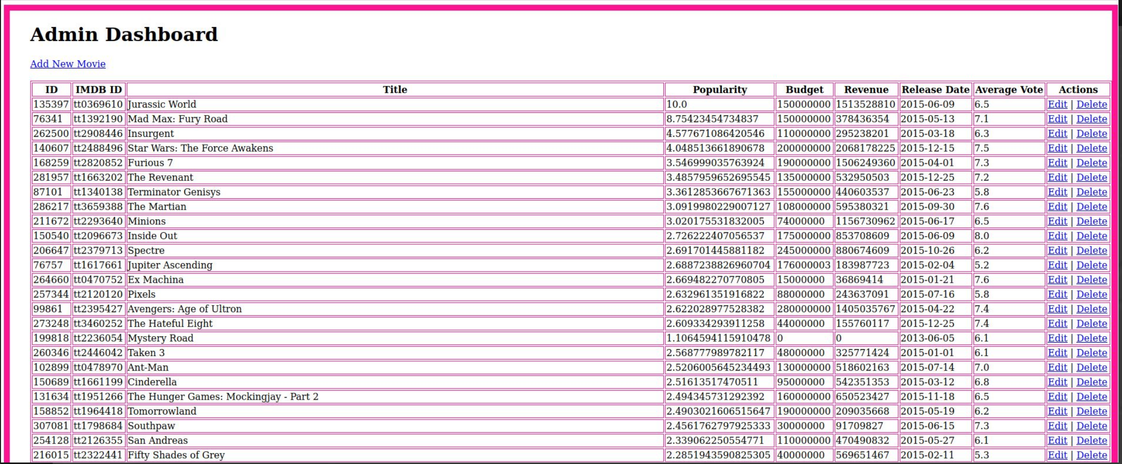


Login and Signup





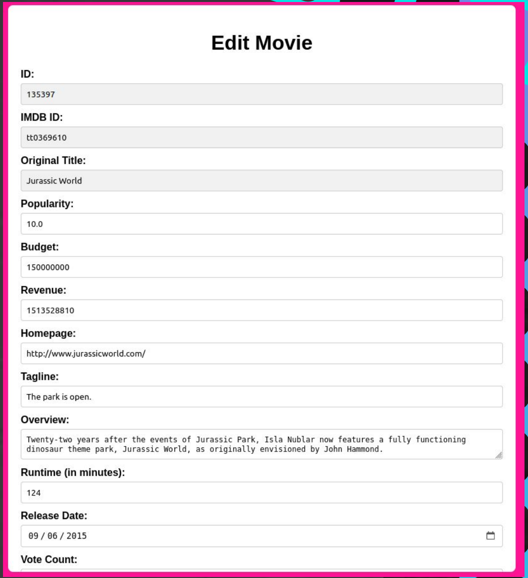
Admin Dashboard



Admin Dashboard

Add New Movie

ID	IMDB ID	Title	Popularity	Budget	Revenue	Release Date	Average Vote	Actions
135397	tt0369610	Jurassic World	10.0	150000000	1513528810	2015-06-09	6.5	Edit | Delete
76341	tt1392190	Mad Max: Fury Road	8.75423454734837	150000000	378436354	2015-05-13	7.1	Edit | Delete
262500	tt2908446	Insurgent	4.577671086420546	110000000	295238201	2015-03-18	6.3	Edit | Delete
140607	tt2488496	Star Wars: The Force Awakens	4.048513661890678	200000000	2068178225	2015-12-15	7.5	Edit | Delete
168259	tt2820852	Furious 7	3.546999035763924	190000000	1506249360	2015-04-01	7.3	Edit | Delete
281957	tt1663202	The Revenant	3.4857959652695545	135000000	532950503	2015-12-25	7.2	Edit | Delete
87101	tt1340138	Terminator Genisys	3.3612853667671363	155000000	440603537	2015-06-23	5.8	Edit | Delete
286217	tt3659388	The Martian	3.0919980229007127	108000000	595380321	2015-09-30	7.6	Edit | Delete
211672	tt2293640	Minions	3.020175531832005	74000000	1156730962	2015-06-17	6.5	Edit | Delete
150540	tt2096673	Inside Out	2.726222407056537	175000000	853708609	2015-06-09	8.0	Edit | Delete
206647	tt2379713	Spectre	2.691701445881182	245000000	880674609	2015-10-26	6.2	Edit | Delete
76757	tt1617661	Jupiter Ascending	2.6887238826960704	176000003	183987723	2015-02-04	5.2	Edit | Delete
264660	tt0470752	Ex Machina	2.669482270770805	15000000	36869414	2015-01-21	7.6	Edit | Delete
257344	tt2120120	Pixels	2.632961351916822	88000000	243637091	2015-07-16	5.8	Edit | Delete
99861	tt2395427	Avengers: Age of Ultron	2.622028977528382	280000000	1405035767	2015-04-22	7.4	Edit | Delete
273248	tt3460252	The Hateful Eight	2.609334293911258	44000000	155760117	2015-12-25	7.4	Edit | Delete
199818	tt2236054	Mystery Road	1.1064594115910478	0	0	2013-06-05	6.1	Edit | Delete
260346	tt2446042	Taken 3	2.568777989782117	48000000	325771424	2015-01-01	6.1	Edit | Delete
102899	tt0478970	Ant-Man	2.5206005645234493	130000000	518602163	2015-07-14	7.0	Edit | Delete
150689	tt1661199	Cinderella	2.51613517470511	95000000	542351353	2015-03-12	6.8	Edit | Delete
131634	tt1951266	The Hunger Games: Mockingjay - Part 2	2.494345731292392	160000000	650523427	2015-11-18	6.5	Edit | Delete
158852	tt1964418	Tomorrowland	2.4903021606515647	190000000	209035668	2015-05-19	6.2	Edit | Delete
307081	tt1798684	Southpaw	2.4561762797925333	30000000	91709827	2015-06-15	7.3	Edit | Delete
254128	tt2126355	San Andreas	2.339062250554771	110000000	470490832	2015-05-27	6.1	Edit | Delete
216015	tt2322441	Fifty Shades of Grey	2.2851943590825305	40000000	569651467	2015-02-11	5.3	Edit | Delete



Contributions

Shivendr - Pre-processing, Schema Design

Sudhin - Visualization, UI, Authentication

Shivendr & Sudhin - SQL Query , Triggers

Thank You